Master's Thesis

A study on manufacturing complexity and difficulty in a mixed model assembly line : Application of Automobile assembly process.

Ikchan Ju

Department of System Design and Control Engineering

Graduate School of UNIST

2016

A study on manufacturing complexity and difficulty in a mixed model assembly line : Application of Automobile assembly process.

Ikchan Ju

Department of System Design and Control Engineering

Graduate School of UNIST

A study on manufacturing complexity and difficulty in a mixed model assembly line : Application of Automobile assembly process.

A thesis/dissertation

submitted to the Graduate School of UNIST

in partial fulfillment of the

requirements for the degree of

Master of Science

Ikchan Ju

07. 08. 2016 of submission

Approved by

Advisor

Nam-Hun Kim

A study on manufacturing complexity and difficulty in a mixed model assembly line : Application of Automobile assembly process.

Ikchan Ju

This certifies that the thesis/dissertation of Ikchan Ju is approved.

07. 08. 2016 of submission

signature

Advisor: Nam-Hun Kim

signature

typed name: Seung-Chul Lee

signature

typed name: Sung-Youb Kim

Abstract

In the automotive industry, most of the major manufacturers have concentrated their capabilities to develop mixed-model production systems as a key enabler of a flexible manufacturing system. With a trend of increasing product variety, the flexible manufacturing system, which produces various products in small volume with limited resources and reasonable cost, becomes the major competitive advantage of manufacturing companies. However, the mixed-model production system meets some problems by an acceleration of the diversification trend. Diversification of products causes a dramatic increase in manufacturing complexity and imposes additional processes with extra cost on manufacturing systems. Nevertheless, quantitative indexes which estimate manufacturing complexity are relatively insufficient. For this reason, a study about manufacturing complexity is needed and this paper is one such effort to estimate manufacturing complexity.

This thesis proposes a reliability based complexity model to estimate the manufacturing complexity of mixed-model production systems in the manufacturing industry and validates it through a simple experiment in a small scale assembly line. After that, an application case study is introduced with real production data from the automotive manufacturing industry. In the case study, the model can compute the reliability of assembly processes from process information of the system. Based on the result, manufacturing engineers can get feedback on such things as the current status of an assembly line or the efficiency of a redesigned system. Furthermore, with accurate and specific process information, the model can forecast unintended costs or errors in the system. For example, the model can anticipate downtime caused by mistakes made by an operator in a mixed-model assembly line.

As a characteristic of the automotive industry, there are lots of models, options and parts and, furthermore, automobiles are composed of numerous parts. Because of that, the manufacturing system is very complicated and estimation of the manufacturing complexity is more significant. For this reason, the reliability based complexity model can contribute to the growth of the automotive industry by providing an opportunity to optimize manufacturing systems as a decision support tool.

Contents

List of Figures

List of Tables

1. Introduction

1.1 Background

In traditional manufacturing field focused on mass production systems to maximize profit and an efficiency of resource management. For the reason, manufacturing companies installed single-model assembly lines and succeeded in minimizing costs with large production volumes. As a result of that, customers were able to get a high quality products at low price. However, nowadays, variety of products is increased because of customer needs, environmental problems, government regulations, and different national policiwp1es. Consequently, existing single-model assembly lines have been replaced by multi-model assembly lines or mixed-model assembly lines.

in the past, Japanese motor companies such as Toyota and Honda had large market shares and led the auto industry with mass production and by maximizing manufacturing efficiency. Meanwhile, a few years ago, BMW said that “every vehicle that rolls off the belt is unique” and the number of possible automobile combinations in the BMW 7 Series alone was roughly 10^{17}. In this way, model variety becomes one of most important criteria which show competitiveness of manufacturing companies.

Figure 1. 1 The examples of causes which make complexity.

These changes help companies manage to resource efficiently and it becomes a foundation to realize a flexible manufacturing system. Mixed-model assembly lines have been developed as a key enabler satisfying customer demand and market trends. But, with the acceleration of diversification, the system meets the problem that manufacturing complexity dramatically increases with the increasing variety of products.

In the automobile manufacturing industry, there are lots of restrictions which increase model/option variety such as strict government regulation of each country, customers' requirements and development of technologies etc. To meet the restrictions, companies can choose to redesign a product to suit all of them. But, it is an inefficient choice in terms of manufacturing cost because the redesigned model should contain many extra systems which are not necessary in some cases. So, to reduce cost and strengthen price competitiveness, most automakers decide to produce various options in a model.

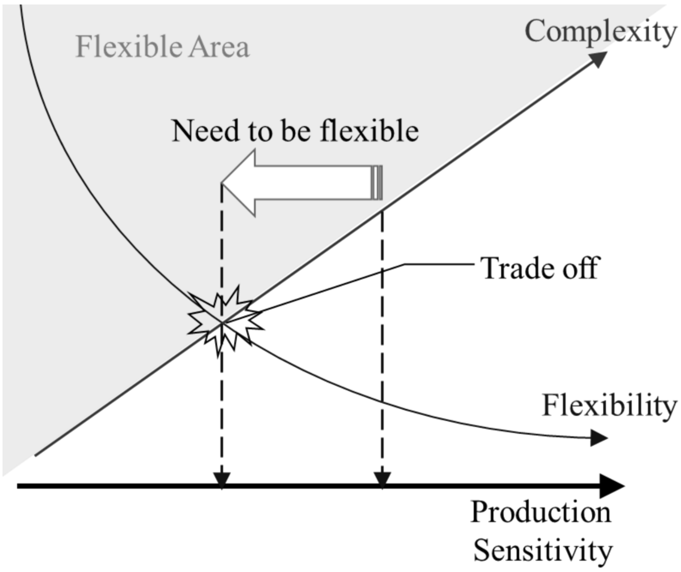


Figure 1. 2 Trade-off between complexity and flexibility(lee, 2015)

For this reason, flexibility and complexity of the manufacturing system become the most important factors. But, unfortunately, they is a kind of trade-off relationship (see Figure 1.2) because complexity is related to how many models/options can be produced in a manufacturing system, and the flexibility is related to how insensitive the system is for the various models and options.

1.2 Motivation

To satisfy the trends of a dramatically changing marketplace, production systems have been changed from single-model to mixed-model production systems. This was an unavoidable decision to survive the rapid development of industry and it has consequentially realized flexible manufacturing systems. The systems can produce various models in a single production line that are composed of a certain number of stations connected in a series. A study defines the role of the station in the mixed-model production system "Each station can process multiple products with the operator selecting an option from many variants of a module and assembling it onto the partially finished product". But, the systems also have problems such as bottleneck, downtime, hereditary error, etc., because the stations in the mixed-model production systems are affected by each other. For example, once a task fails or is delayed, the effect leads to other errors or an overall delay of the line as a downtime. In this way, unexpected errors from a variety of products make the system inefficient. Therefore, a study on the effect of complexity is a meaningful challenge in mixed-model production systems.

Manufacturing complexity can be analyzed with two types of approaches, such as physical and functional domains. In the functional approach, complexity represents an uncertainty triggered by functional specifications like system design. In the other approach, complexity covers the environment and contents of the system; structure & configuration of the manufacturing system resources and the number of products, parts, processes, and tools. In this thesis, to analyze manufacturing complexity, the physical approach is concentrated on because this idea deals with the changes of the complexity by the growth of the model and option variety in the automobile production system.

When new models or options were launched in traditional manufacturing systems, most engineers depended on qualitative indicators such as their experiences, intuitions, and know-how. For example, when the product volume ratio is rearranged, manufacturing engineers need to evaluate the complexity and optimally redesign a new line balance to mitigate it as soon as possible. In the rearrangement process, the complexity of overloaded stations is mitigated to relatively less loaded stations and the basis of the decision is almost based on the experience or intuition of operators and engineers. These types of solutions, which are sometimes referred to as trial and error, mostly take more than 3 months to mitigate the manufacturing complexity as best as possible. During the process, manufacturing companies consume lots of cost and resources to identify the best practice. If there is a way to estimate the complexity in the early steps, then companies and engineers can reduce cost and time to find an optimal solution of the line balancing problem.

1.3 Research objective

The manufacturing complexity of mixed-model production systems depends on the variety, the process information, and the manufacturing difficulty of the system. Numerous studies have tried to define the relation between those factors and manufacturing complexity. By the efforts, there were lots of meaningful outcomes to estimate the manufacturing complexity, such as choice complexity based on informative entropy and the reliability based complexity model. However, sadly, application case studies are relatively insufficient in the real field. For this reason, this thesis proposes a model to estimate the manufacturing complexity in real production field and shows a case study of the model with real manufacturing information data.

Main objectives of this study is as follows:

1) Proposing a reliability based complexity model, which can estimate the manufacturing system, and validating the model with toy example and simple experiment.

2) Applying the model to a real production system in an automobile manufacturing industry and estimating the manufacturing complexity of mixed-model assembly line in the system.

3) Presenting potential development and application method in further manufacturing industries.

2. Literature survey

2.1 Manufacturing complexity in the automotive industry

In manufacturing processes, there are strong relationships among product design, production equipment, material and support systems. As customer demand on the variety of model and option is increasing, the elements cause implications in manufacturing processes as elements involved with all levels of an organization in the system (Urbanic et al., 2006). Each element of the processes have tangible information but the relationship of the elements are intangible. Therefore, the manufacturing system is complicated and the complexity is difficult to study and analyze.

Figure 2. 1 Elements of manufacturing processes

To analyze the manufacturing complexity, quantifying the complexity is prior to others and it required to determine measuring technique from various approaches to define manufacturing complexity (Urbanic et al., 2006). So, this section presents a definition of complexity and mixed-model assembly systems which are main target to be analyzed in this thesis.

2.1.1 Definition of complexity

As shown at Figure 2.2, to estimate complexity of products, assemblies or compartments, the manufacturing complexity is defined in terms of both functional and physical domains. In this thesis, the definition of complexity on the physical domain is determined by various approaches of the applications. However, recent researches have tried to find that recognition and management of complexity depends on the quantity, diversity and content of the information which is represented, as one of efforts to produce the desired result (Urbanic & ElMaraghy, 2006).

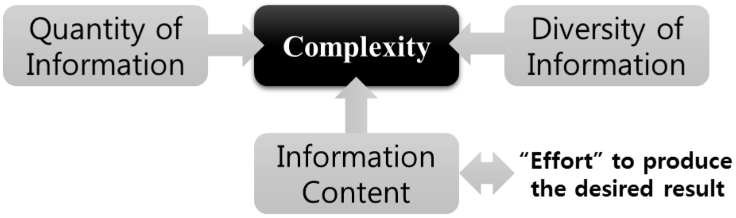


Figure 2. 2 Elements of complexity (Urbanic & ElMaraghy, 2006)

Another research has defined that complexity is a measuring index which analyzes how a variety of products or models complicate the manufacturing system (Zhu et al. 2008). Consequently, the manufacturing complexity depends on the magnitude of the manufacturing information, which consists of details of the task, cycle time and the number of options available. Most of the manufacturing complexity studies are considering those elements.

2.1.2 Mixed-model assembly systems

When Henry Ford created the moving assembly lines system driven by using a conveyor belt for manufacturing cars, the line was a dedicated production system for single products which have a high production volume (Koren, 2010). However, as a product variety is increased to satisfy the market demands in automotive industry, many kinds of products have been produced in a moving assembly line. It was named as 'Mixed-model assembly line' and this term was used extensively in many researches and dissertations about the analysis of manufacturing systems. Basically, the 'Mixed-model assembly line' has a certain number of independent stations which are connected to each other in series. In the system, an operator completes a certain assembly process with selecting a required part. And, after finishing the processes, the product is passed to the next station.

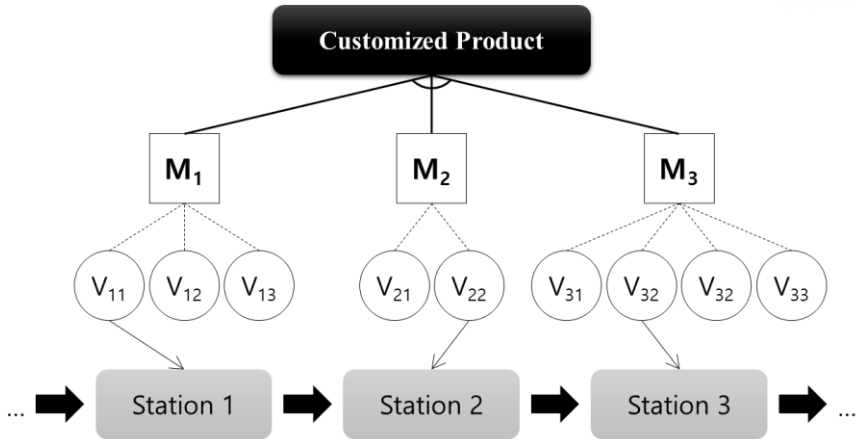


Figure 2. 3 Illustration of mixed-model assembly line (Zhu et al., 2008)

Figure 2.3 illustrates a structure of the mixed model assembly line. In this assembly line, there are three models of the product which are denoted by M_i (jth model). Each model has j variants, it is denoted V_{ij} (jth variant of ith model) (Zhu et al., 2008). Even if a moving assembly line mass produces one product, there is a shortcoming. If a certain malfunction does not meet the demands of the market and product varieties arises in a station, the whole production line will stop, causing over-cycle time to occur. Therefore manufacturers are striving to overcome this problem as well as maintain the flexibility of operators at each station, by applying diverse configurations of stations within a mixed model assembly system, including serial, parallel and hybrid configurations (Wang, 2010). Complexity in mixed model assembly line degrades the system performance. To help lower this degradation, manufacturing engineers would rearrange the configuration of stations by line balancing, or sometimes sequence the components which are assigned for assembly in advance.

2.2 Approaches to measure complexity

As shown in Figure 2.1, the quantity, diversity and content of information influence the manufacturing complexity. These factors decrease productivity by inducing uncertainties in the manufacturing process, therefore, it is essential that time-coordination, validity and flexibility are considered in the manufacturing process. However, current countermeasures against complexity are completely dependent on skilled human resources. Once effective management of the manufacturing complexity fails, the reliability of the system is detrimentally affected, as well as the quality and throughput of the productivity (Urbanic et al. 2006).

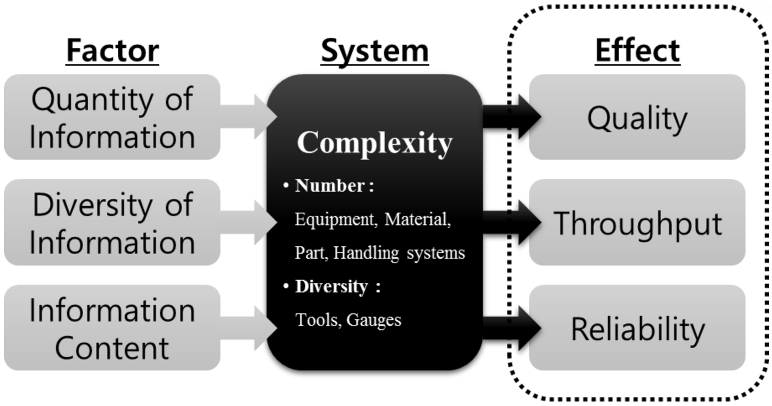


Figure 2. 4 Factors of complexity and their effects on the system.

Throughout the evaluation of the effects caused by the factors on the system, the complexity of the whole system or each process can be measured. In previous studies, the factors which influence the system, are calculated as an information entropy and the effects from the complex system, are estimated as a throughput and reliability.

2.2.1 Information theory (Information entropy)

Some researchers have tried to measure the complexity of manufacturing by using the entropy method in information theory. The term “information entropy” can be defined as an index of uncertainty measurement on the outcome of a random event in the context of communication systems (Shannon, 1948). In the area of product design, information entropy was defined as a measure of uncertainty in understanding what we want to know or in achieving a functional requirement (FR) (Suh 2005). According to Shannon, the entropy (H) of a discrete random variable Y with possible values {y1, ..., yn} and probability mass function P(Y) is obtained by the following equation:

$$\mathrm{H(Y)} = \sum_i P(y_i)I(y_i) = -\sum_i P(y_i)log_b P(y_i)$$

Here, I is the information content of Y and b is the base of the logarithm. The selection of the b value determines the measurement of information content in a random variable Y; b= 2 is one of the most common values where the information content stored in Y is measured in bits (Shannon, 1948). In the context of manufacturing, specifically the assembly line, operator choice complexity by module (part) variety can be explained by uncertainty or randomness of the selection process (Zhu et al., 2008). For example, in a mixed model assembly, the operator should select the right component for the assembly within the acceptable time window offered to that specific task ensuring the optimality of the flow. Meanwhile, when the amount of variety increases, the uncertainty increases and the components selection generally takes additional time, otherwise risking the effectiveness of the process.

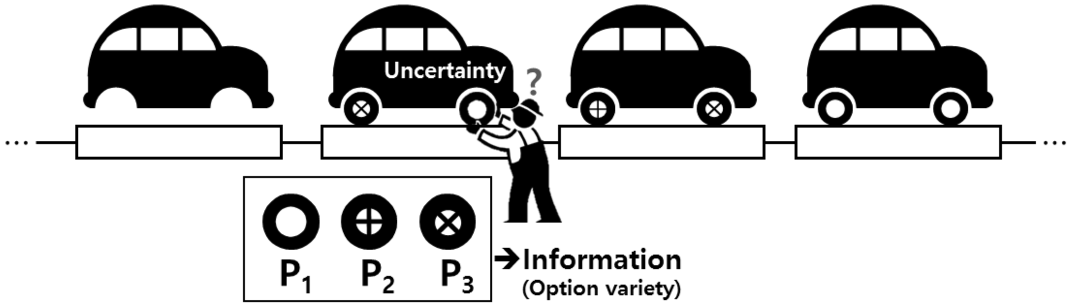


Figure 2. 5 An example of operator choice complexity.

There is a simple example for clear understanding of information theory. As shown in Figure 2.6, in order to get the correct answer of sixteen numbers, four questions which require an answer of either 'Yes or No', are required.

1) Is the number at the upper half side? → Yes → Answer is one of 1, 2, 3, 4, 5, 6, 7, and 8.

2) Is the number at the right half side among them? → No → Answer is one of 1, 2, 5, and 6.

3) Is the number at the upper half side among them? → No → Answer is one of 5 and 6.

4) Is the number at the right half side among them? → Yes → Answer is 6.

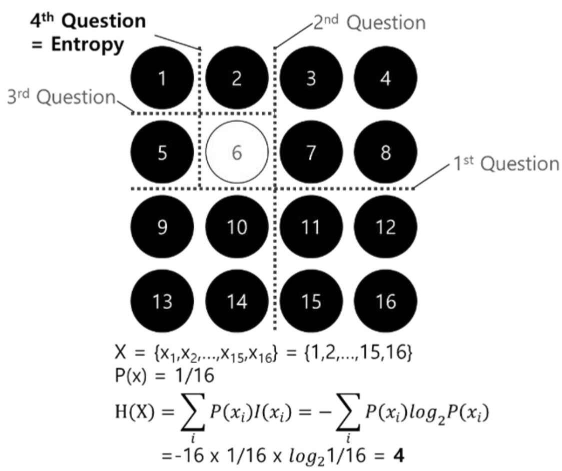


Figure 2. 6 Simple example of information entropy (Lee 2015).

Since there are two options for the answer, the base of the logarithm is 2. Four questions must be asked in order to determine the answer, therefore the information entropy in this case is 4.

2.2.2 Entropy model of mixed-model assembly system

In a mixed model manufacturing system, although the stations in the process are arranged serially, a number of configurations can exist for the process. For instance, when there are four stations with mixed assembly process, six configurations are able to be considered as shown in Figure 2.7. This means that configurations have a substantial impact on the productivity (Wang 2011).

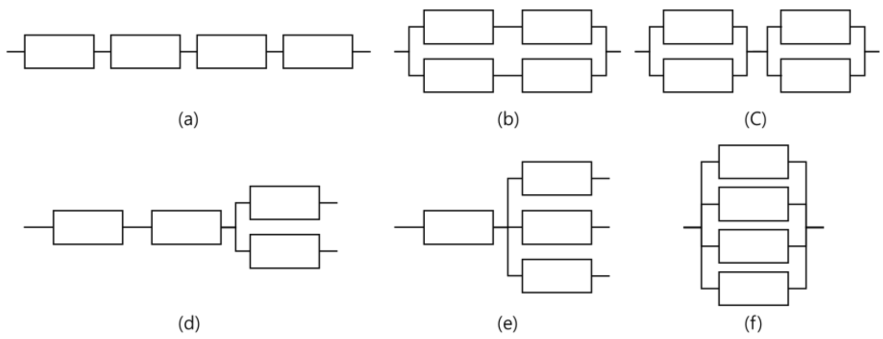


Figure 2. 7 Different configurations for four stations. (Wang 2001).

Therefore, when measuring the complexity induced from product variety, system configuration should be considered. There are three major configurations; serial, parallel and hybrid. Assuming a product with n modules and module *i* has different variants $V_i (i = 1, \cdots, n)$. Suppose the variants of the nth module is considered to be a distinct product variant of any configuration. Accordingly, total number of product variants is as follows:

$$N = \prod_{i=1}^{n} V_i$$

where it is assumed that the assembly sequence is independent of the configurations. Also it is assumed that the customer demand does not influence the *N* variants, where the total probability of the total demand on the variant *j* is q_j, ($j = 1, \ldots, N$). Here, $\sum_j q_j = 1$. Therefore demand mix for the N variants is specified as vector $Q = (q_1, \cdots, q_N)$. Figure 2.8 illustrates a simple example of four modules with two variants. When n = 4 and V_i = 2, *i* = 1,2,3,4, total variants of the product is $N = 2^4$ (Wang 2011).

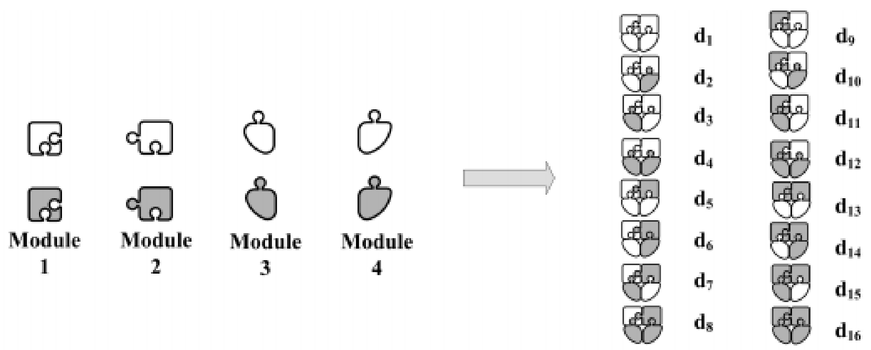


Figure 2. 8 Simple example of 4 modules & 2 variants with total variants (Wang 2010).

When the product has four modules which are assembled at four stations, the cycle time of a station is equal to T at all stations, where the total assembly cycle time for each configuration is shown in Figure 2.9.

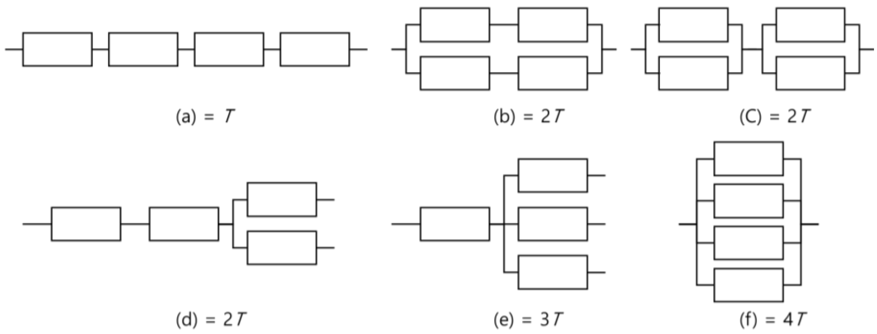


Figure 2. 9 Total cycle time with 4 modules and cycle time T at each station.

Table 2.1 shows the calculation of the total assembly cycle time according to station configuration. The number of modules assembled at station *k* is denoted by n^k, while the assembly cycle time of station k, (k = 1, …, n) is denoted by T^k.

Table 2. 1 Description of serial, parallel and hybrid configurations (Wang 2010).

	Number of modules assembled at station k	Assembly cycle time of station k
Serial	$n^k = 1$	$T^K = T$
Parallel	$n^k = n$	$T^K = n \cdot T$
Hybrid	$1 \le n^k \le n\text{-}1$	$T^K = n^k \cdot T$

If several modules are assembled at station k, the total number of nk modules in all feasible configurations is computed as follows:

$$N^k = \prod_{i \in A_k} V_i$$

while the demand fraction on the variant v of k stations is computed as follows:

$$q_v^k = \sum_{j \in L(v)} q_j$$

where L(v) denotes the set of the variants for the product.

The information theory can be used to evaluate the uncertainty from random event choosing a right part among the different variants. Thus entropy function to measure the complexity of station k is as follows:

$$H^k = -\sum_{m=1}^{M} p_m \log_2 p_m$$

In this function, the denotation M represents the number of different variants which require selection and pm is the probability of demand on the variant m (m = 1,…,M).

If the mixed assembly has a serial configuration where no losses occur, then the system complexity is computed by the following function;

$$H_{Serial} = \sum_{i=1}^{n} H^i = -\sum_{i=1}^{n}\sum_{v=\Delta}^{V_i} q_v^i \log_2 q_v^i$$

In the case of a mixed assembly system having a parallel configuration at the same assembly station and n modules are assembled at each station, the complexity is computed as follow functions;

$$H_{paralle} = \sum_{i=1}^{n}\sum_{v=\Delta}^{N}\left(\frac{q_v^i}{n}\right)\cdot \log_2\left(\frac{q_v^i}{n}\right) = -\sum_{j=1}^{N} q_j \log_2 q_j + \log_2 n$$

When the mixed model assembly line has a simple hybrid configuration, the complexity can be computed by dividing serial and parallel configuration. However in case of complicated hybrid configuration, it is required to simplify the configuration to a serial or a parallel configuration by substituting two or more stations as shown in Figure 2.10 (Wang 2010).

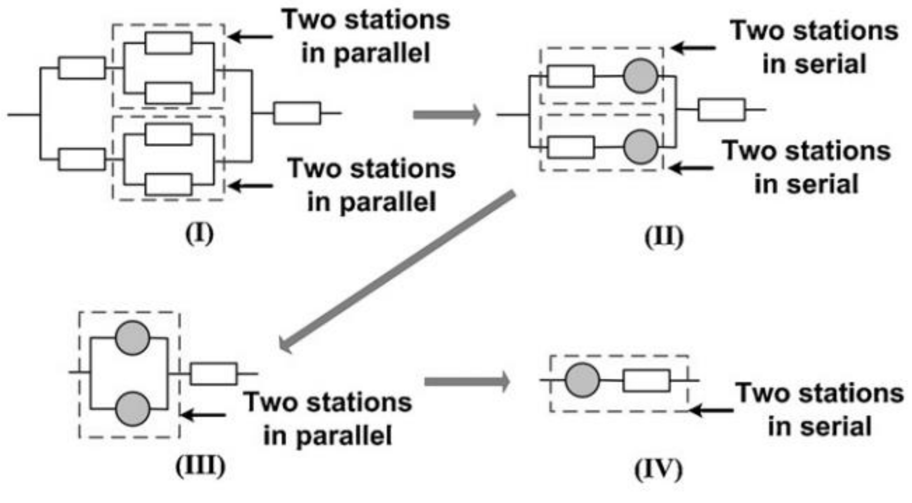


Figure 2. 10 An example to calculate the complexity of a hybrid configuration (Wang 2010).

2.2.3 Reliability model of manufacturing system

In mixed model assembly systems, complexity has a negative effect on the productivity and the previous chapter deals outlines the method of determining the complexity of a system from information entropy. However this entropy is not a general indicator that is used to evaluate the level of complexity intuitively. In this sense, the human cognitive reliability model introduced by Yang et al. (1997) is a useful approach to analyze the extent of the system in terms of intricacy. They have studied the effect of the operator's diagnosis to the system reliability in the decision making process. According to their study, human cognitive reliability data follows Weibull and Lognormal distributions. From the cycle time model according to the system configuration, the cycle time T^k at station k leads to the function $T^k = n^k \cdot T$ based on Table 2.1, where n^k represents the number of modules which is assembled at station k. T^k is the maximum time frame that is required for the completion of assembly. The work includes the following tasks; s/he should select the right option and then assemble it on the product within the given time limit. In another study, the average reaction time for choosing the correct option according to the human decision making process, has a linear relationship with the information entropy delivered by stimulus (Hyman 1953). In this sense, the selection time is equated with the delivery time by stimulus for information entropy. Therefore, following equation is valid;

$$TS^k = a + b \cdot H^k$$

where TS^k is the average time to select the right option, i.e. reaction time. H^k is the complexity of the station, or the information entropy in the station of its own configuration, while a and b are constants which are assumed to be homogeneous operators. And also, if all modules have the same assembly time, the assembly time at station k can be computed by;

$$TA^k = n^k \cdot d$$

where TA^k is the assembly time at station k and d is the assembly time for a module.

There are two critical factors that influence the station reliability. Firstly, the ratio of reaction time TS^k for the correct option and the time difference between one cycle time T^k and assembly time TA^k. is represented by $b \cdot H^k/(T^k - TA^k)$.

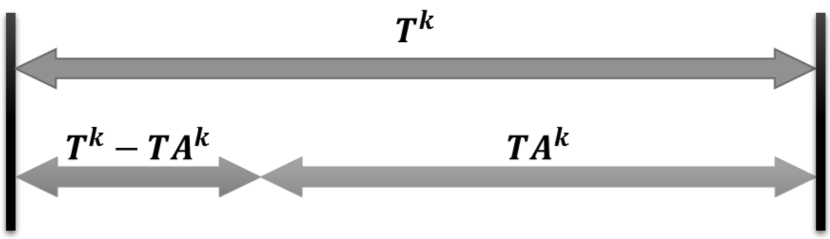


Figure 2. 11 Reaction time.

Secondly, the operator's fatigue effect is distinguished by two either physical or mental fatigue. According to the study of Bystrom et al. (1994), when assembly time is more than 17% of the cycle time at a station, operators experience physical fatigue. Mental fatigue depends on the required time for cognitive activity to select right option. The reliability R^{k} considering the mental fatigue of operator at station k, is given by the following equation;

$$R^k = e^{-\left(\frac{bH^k}{[(T^k - TA^k)\cdot\eta(H^k)]}\right)^\beta}$$

where $\eta(H^k)$ is the fatigue effect of the operator at station k. When H^k is zero and the reliability R^k of the process is 1, there is no complexity at the station k (Wang 2011).

3. Reliability based complexity model in mixed-model assembly line

Mass customization systems aim to produce various products with a reasonable cost of mass production system. As a key enabler of that, mixed-model production systems are spotlighted and have been developed to maximize the efficiency of the system. However, a large variety leads to some problems to mixed-model production systems, including lowering productivity, complicating assembly processes, degrading quality, etc. For this reason, Many studies have been conductedto analyze and predict the complexity of a manufacturing system. But, the operator-oriented approach is relatively insufficient and has some problems because of the way it is necessarily affected by human error. Nevertheless, operator-oriented complexity studies have steadily progressed and this chapter presents one such effort.

3.1 Manufacturing systems of the automotive industry

In this thesis, the major objective is the modeling of manufacturing complexity in the automotive industry with a consideration of entropy and reliability models. For understanding of the automobile manufacturing system, this section explains the actual manufacturing process, focusing on the assembly process.

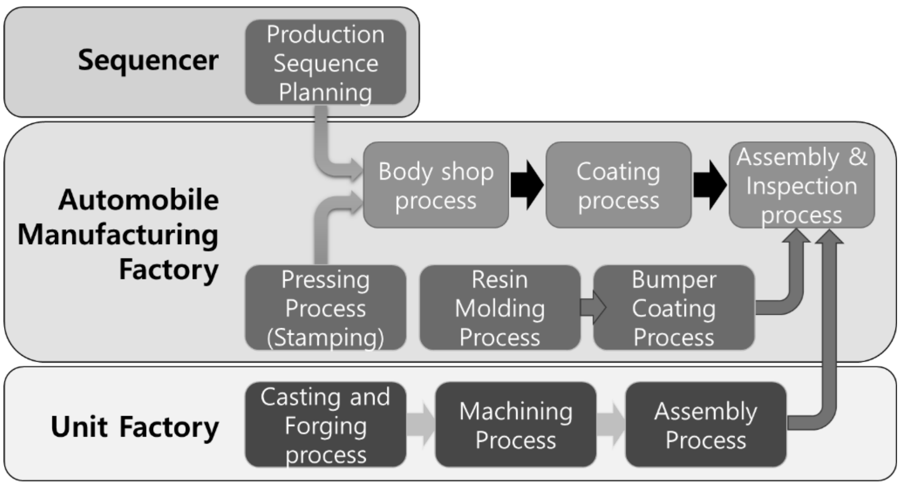


Figure 3. 1 Process map for automobile manufacturing

Figure 3.1 shows a brief process map for the automobile manufacturing system. The automotive manufacturing process consists not only of various sub-processes, but also many lines and stations where the processes are handled. The following figure is an illustration of a prominent examples of the body shop process in the automobile assembly system. The body shop process has various sub-processes as shown in Figure 3.2 and the sub-processes also have many stations for them. Most of the assembly lines follow typical automobile manufacturing processes regardless of the manufacturer, but the contents of the processes at the stations are distinct from others, according to the automobile manufacturers, because the tasks and number of stations depend on the product design and the manufacturing techniques of the manufacturers.

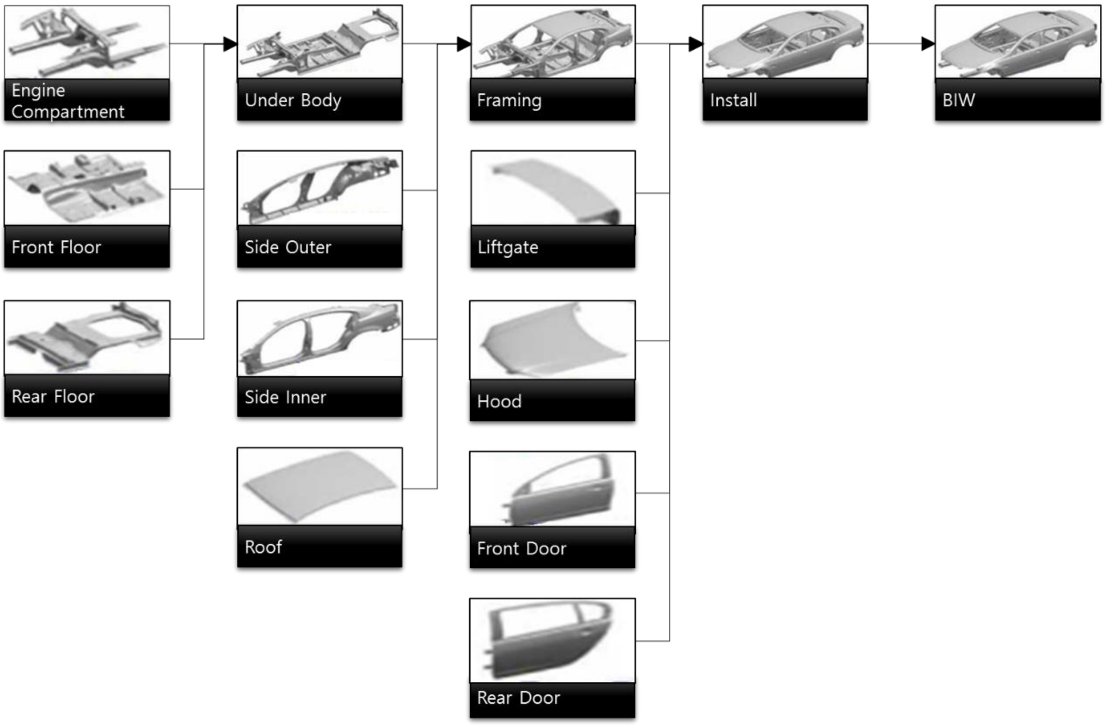


Figure 3. 2 Typical process of automobile body shop plant

In automobile manufacturing factories, the most prior process can be defined as the assembly process with regards to the manufacturing complexity. Because the process has some severe factors to trigger the complexity such as numerous option variations, manufacturers have tried to mitigate complexity and enhance the flexibility of the production system. Product sequencing planning is a typical example, as shown in Figure 3.1. In the case of several option variations, the options stream onto the conveyor according to the sequence planning. Sequence strategy is only available for ‘just in time’ options regarding the delivery time. Numerous common options like bolts, nuts and fastener types, are stacked next to the station and the selection time for the right assembly options for these parts increase the manufacturing complexity. In a real automotive assembly system, there are many solutions to mitigate the manufacturing complexity, when volume changes or new models are launched in an existing production line. But, it leads to extra cost on the manufacturing system. So, manufacturing engineers are required to identify the most effective and low-cost solution to mitigate the complexity.

3.2 Entropy Approach(Operator Choice Complexity)

In automobile assembly processes, operators meet lots of choices caused by a variety of products. Basically, in the processes, they should check a model of the current product and also confirm its option. Next, the operators judge what they should do in this step, which part they should select, which tool they should use, and which point they should check. In this way, operators consider lots of things in the processes and it means that they could feel high complexity in automobile assembly systems. To measure and distribute the complexity, this thesis takes 'Informative entropy' of Shannon (1948) which measures the uncertainty of a system from the amount of its information.

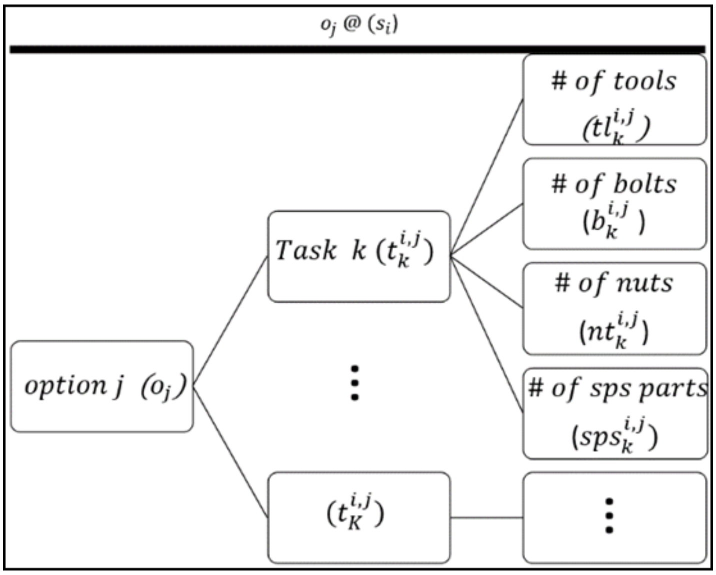


Figure 3. 3 Entropy components

In the automotive assembly line, there are many sources which can make operators feel complex such as variation of model and option. As shown in figure 3.3, a number of compositions are induced by the variations and operators are placed in a situation that they should select proper tasks and parts in various probabilities.In addition, different models/options sometimes mean that operators suffer from selecting not only tasks and parts but also tools, bolts and nuts. That is, the number of cases in a mixed-model assembly line makes the manufacturing complexity.

Table 3. 1 Structure of variants which compose probability and entropy

	Model *j*								
	Option 1				⋯	Option *k*			
	Parts	Bolts	Nuts	Tools		Parts	Bolts	Nuts	Tools
Station 1	$pt_{j,1}^{1}$	$bt_{j,1}^{1}$	$nt_{j,1}^{1}$	$tl_{j,1}^{1}$		$pt_{j,k}^{1}$	$bt_{j,k}^{1}$	$nt_{j,k}^{1}$	$tl_{j,k}^{1}$
⋮					⋱				
Station *i*	$pt_{j,1}^{i}$	$bt_{j,1}^{i}$	$nt_{j,1}^{i}$	$tl_{j,1}^{i}$		$pt_{j,k}^{i}$	$bt_{j,k}^{i}$	$nt_{j,k}^{i}$	$tl_{j,k}^{i}$

As shown in table 3.1, the process for estimating entropy starts from the station level and progresses to the overall system level. And computation of the entropy starts from the model confirmation level and moves to the part selection level. The elements of the manufacturing process in the station: model ratio, option ratio, the number of parts, the number of bolts, the number of nuts, the number of tools, etc. Let X^i be a set of variables inducing the uncertainty at station *i* and $P(X^i)$ be a function of probability of the station *i*. And X^i is defined as $X^i = \{M^i, O^i, Pt^i, Bt^i, Nt^i, Tl^i\}$, the values $M^i, O^i, Bt^i, Nt^i, Tl^i$ respectively mean as follows,

M^i: Model ratio at station *i*.

O^i: Option ratio at station *i*.

Pt^i: The number of individual parts at station *i*.

Bt^i: The number of individual bolts at station *i*.

Nt^i: The number of individual nuts at station *i*.

Tl^i: The number of individual tools at station *i*.

With the set X^i, the information entropy can be computed and the model is defined as follows,

$$H = \sum_i H(X^i) = -\sum_i \sum_j \sum_k P(x_{j,k}^i) \log_2 P(x_{j,k}^i)$$

$$P(x_{j,k}^i) = M_j^i \cdot O_k^i \cdot \frac{pt_{j,k}^i}{Pt^i} \cdot \frac{bt_{j,k}^i}{Bt^i} \cdot \frac{nt_{j,k}^i}{Nt^i} \cdot \frac{tl_{j,k}^i}{Tl^i} \quad where:$$

$\mathrm{H}(X^i)$: Informative entropy at station *i*.

$p(x^i_{j,k})$: Probability for option k of model j at station i.

X^i : A set of variables inducing the uncertainty at station i.

$x^i_{j,k}$: A set of variables inducing the uncertainty for option k of model j at station i.

$$x^i_{j,k} \in X^i \ , x^i_{j,k} = \{M^i_j, O^i_k, pt^i_{j,k}, bt^i_{j,k}, nt^i_{j,k}, tl^i_{j,k}\}$$

M^i_j: Model ratio for model j at station i.

O^i_k: Option ratio for option k at station i.

$pt^i_{j,k}$: The number of individual parts for option k of model j at station i.

$bt^i_{j,k}$: The number of individual bolts for option k of model j at station i.

$nt^i_{j,k}$: The number of individual nuts for option k of model j at station i.

$tl^i_{j,k}$: The number of individual tools for option k of model j at station i.

3.3 Reliability Approach

At each decision point, operators must select the right parts and tools and complete processes within a given time. For this reason, system performance and complexity seems to be influenced by the number of alternatives at the station and a given time for the decision without processing time. With the entropy approach, informative entropy can measure the complexity induced by the information of the system. However, the entropy is not enough to estimate the performance of the system because the entropy is not the only one which affects the complexity operators feel in the assembly process. Decision time can be considered as one of the other factors that affect the complexity. Assume that there are two assembly systems and their elements are exactly the same including the entropies, but the time given for decision and selection is different as one system gives enough time and the other system gives the time tightly. Then, the answer to the question "which system shows better performance without considering the amount of production?" is trivially the system which has enough time. With this viewpoint, Yang et al. (1997) suggested that Weibull or lognormal distributions can be used to fit human cognitive reliability and for modeling the operator's reliability in the decision making process. If the time given to make a choice decreases, then the reliability of the choice also decreases. And, as already described in chapter 2, physical and mental fatigue are also considered to estimate the reliability. And fatigue can be considered that they are induced by difficulty of the process including mental and physical issues. The fatigue effect ($\eta(X^i)$) is handled more specifically in next section.

The reliability of station i can be computed as follows:

$$R^i = e^{-\left(\frac{T_S^i}{[(T^i - T_A^i)\cdot\eta(X^i)]}\right)^\beta} \ where:$$

R^i: Reliability of station *i*.

T^i: Cycle time of station *i*.

T_A^i: Actual assembly time without non-valuable process of station *i*.

$T^i - T_A^i$: Available time to make a selection of station *i*.

$T_S^i = a + bH^i$: Expected reaction time to select of station *i*. Coefficient a and b are ergonomics constants (Hyman, 1953),

$\eta(X^i)$: Fatigue effect induced by difficulty of station *i*.

β: Shape parameter of the Weibull distribution

In this model, the expected reaction time to select the right parts is computed as $T_S^i = a + bH^i$. In this computation, coefficient a and b mean ergonomic characteristics of each operator, which can be defined more accurately by an individual experiment. But, in the real field, it is estimated by several experiments of standard operators because the individual experiment is too hard and inefficient a process. However, if companies can record and trace individual performances, this model becomes more correct and it can also be used as a job allocation support tool. And, about the shape parameter of the Weibull distribution, human cognitive reliability follows an increasing trend of hazard rate. Thus, the parameter may be larger than 1($\beta \geq 1$), depending on the process characteristics. However, in this study, a hazard rate of the assembly process is assumed as constant, the parameter is set as $\beta = 1$.

3.4 Difficulty issues in manual assembly process

In manufacturing processes, operators feel fatigue from many elements of the manufacturing system. Manufacturing difficulty can be considered as one of key factors which lead to fatigue among operators. In an assembly line, operators can feel fatigue when they are pressed for time, carry out heavy parts, confirm model or option which are rarely produced, select the proper part in lots of parts, and concern some errors during operation. There are lots of reasons that operator feels fatigue, and they can be classified as perceptual and physical difficulties. This thesis proposes a fatigue effect model considering difficulty which covers perceptual and physical difficulties in an assembly line.

In some studies about fatigue effects, physical fatigue is sometimes ignored because it is considered as an acceptable point (Bystrom et al. 1994, Wang 2011). Lee (2015) defined the fatigue effect as a decreasing function of the entropy, $\eta(\mathrm{H}(X^k)) = 1/\mathrm{H}(X^i)$, for reliability computation in the assembly line. The fatigue effect model proposed by this thesis is based on his model and it is computed as follows:

$$\eta(X^i) = \left(\frac{1}{d^i \cdot H(X^i)}\right)^{\alpha} \; where :$$

$\eta(X^i)$: Fatigue effect index of station *i*.

$H(X^i)$: Information entropy of station *i*.

d^i: Perceptual difficulty coefficient of station *i*.

α: Sensitivity coefficient of fatigue effect on the system

3.5 Proposed model to estimate the complexity in the mixed-model assembly line

As the proposed model of this thesis, the reliability based complexity model is composed as follows

$$R^i = e^{-\left(\frac{[a+b\cdot H(X^i)]\cdot[d^i\cdot H(X^i)]^{\alpha}}{T^i - T_A^i}\right)}$$

R^i: Reliability of station *i*.

$H(X^i)$: Information entropy of station *i*.

T^i: Cycle time of station *i*.

T_A^i: Actual assembly time without non-valuable process of station *i*.

$T^i - T_A^i$: Available time to make a selection of station *i*.

a, b: Ergonomic coefficients of an operator.

d^i: Perceptual difficulty coefficient of station *i*.

α: Sensitivity coefficient of fatigue effect on the system

To validate this model, a simple experiment (one factor and three level) was conducted in a small scale assembly system. The assembly line has fourteen assembly processes including part selection processes, and there are forty one kinds of parts. All subjects complete the assembly processes, including part selection, under three cases dependent on support systems for part selection. As shown at figure 3.4, the first case is called a "Randomized system" in which the subject should search and select the right parts from a tray of jumbled parts. The second case is known as an "error proofing system (EPS)" where all parts are allocated among the same parts in a fixed layout and a guide monitor presents required parts and volumes with the layout. Lastly, the third case is called the "part sequencing system". In the case, all the required parts are supplied automatically. So, subject do not need to accomplish the part selection process. The design of this experiment is randomized to block an error of order, and six subjects participated in the test (4 males and 2 females).

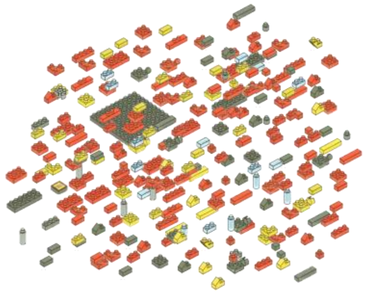
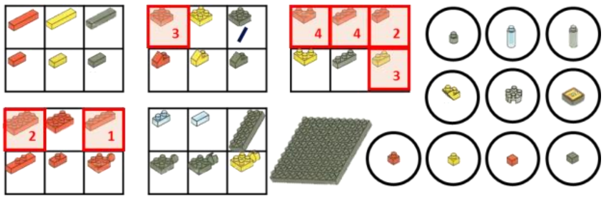
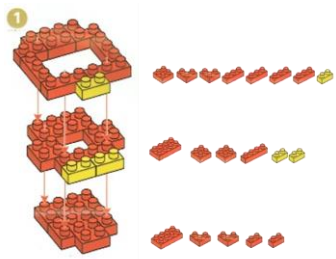
	**Case 1:** **Randomized system**
	**Case 2:** **Error proofing system (EPS)**
	**Case 3:** **Part sequencing system**

Figure 3. 4 Cases of the experiment.

As a result of the experiment, the processing time of each process is recorded and the result is shown in table 3.2. The data in the table is an average of the processing time of each station and case. Trivially, the result shows a trend of processing time (Case 1 > Case 2 > Case 3) at most stations.

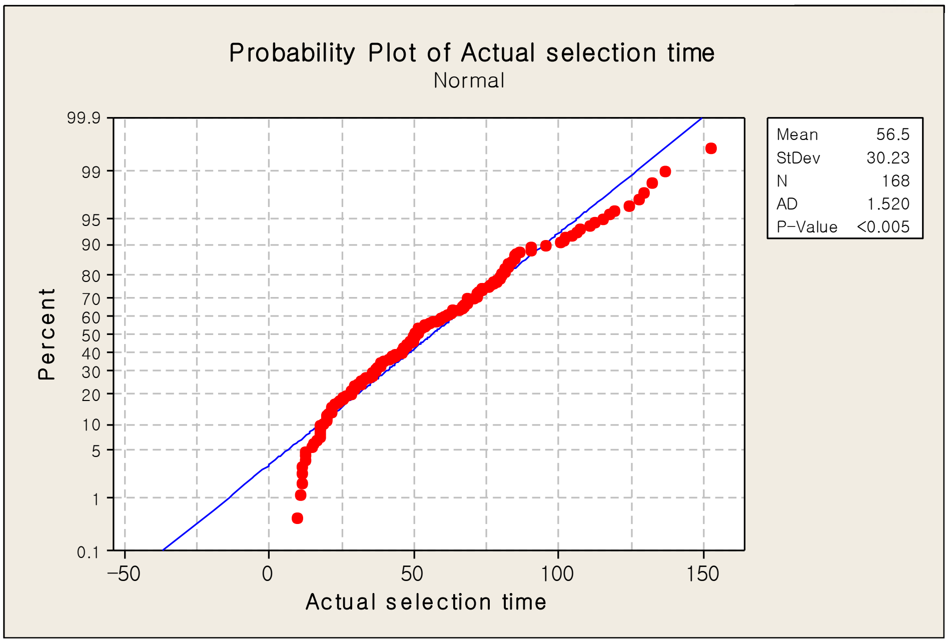


Figure 3. 5 Probability plot of actual selection time.

Table 3. 2 Result of paired t-test

	N	Mean	StDev	SE Mean
Manual	84	67.49	33.25	3.63
EPS	84	45.51	22.12	2.41
Difference	84	21.98	23.2	2.53
95% CI for mean difference: (16.94, 27.01)				
T-Value = 8.68 P-Value = 0.000				

Table 3. 3 Result of the experiment

	Case 1	Case 2	Case 3
S1	257.8	221.7	222.5
S2	292.0	259.8	150.0
S3	227.8	162.8	127.3
S4	283.5	286.0	157.2
S5	33.2	31.0	20.7
S6	155.8	144.0	93.7
S7	145.5	76.3	50.2
S8	133.0	100.0	73.2
S9	279.0	311.5	184.0
S10	304.0	273.0	156.3
S11	193.5	177.2	124.7
S12	64.3	59.5	40.3
S13	283.0	263.3	185.5
S14	269.3	251.2	177.5

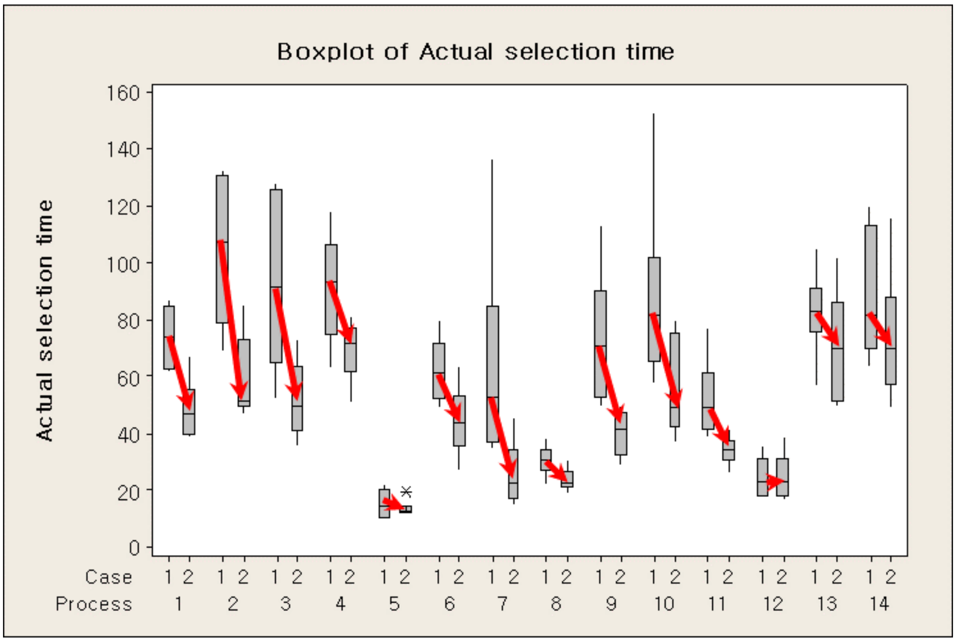


Figure 3. 6 Displacement of actual selection time

As a first step to estimate the complexity, the entropy is computed by the information entropy model $H = \sum_i H(X^i) = -\sum_i \sum_j \sum_k P(x^i_{j,k}) \log_2 P(x^i_{j,k})$. To compute the entropy, probabilities of the parts are needed and the probabilities in table 3.3. In this experiment, there is no probability and entropy in case 3 because the case don't have part selection processes. So, case 3 will be ignored from now on.

And below table 3.3 shows the probability at each station by the cases. For some parts, the probability of case 2 is larger because portions of the parts are larger than other parts.

Table 3. 4 Probabilities of each case and part

	Case 1	Case 2
Part 1	0.003155	0.02439
Part 2	0.012618	0.02439
Part 3	0.015773	0.02439
Part 4	0.012618	0.02439
Part 5	0.014196	0.02439
Part 6	0.009464	0.02439
Part 7	0.011041	0.02439
Part 8	0.050473	0.02439
Part 9	0.01735	0.02439
Part 10	0.025237	0.02439
Part 11	0.023659	0.02439
Part 12	0.022082	0.02439
Part 13	0.022082	0.02439
Part 14	0.015773	0.02439
Part 15	0.037855	0.02439
Part 16	0.080442	0.02439
Part 17	0.009464	0.02439
Part 18	0.05205	0.02439
Part 19	0.053628	0.02439
Part 20	0.018927	0.02439
Part 21	0.023659	0.02439
Part 22	0.015773	0.02439
Part 23	0.020505	0.02439
Part 24	0.050473	0.02439
Part 25	0.022082	0.02439
Part 26	0.01735	0.02439
Part 27	0.047319	0.02439
Part 28	0.009464	0.02439
Part 29	0.012618	0.02439
Part 30	0.029968	0.02439
Part 31	0.050473	0.02439
Part 32	0.011041	0.02439
Part 33	0.037855	0.02439
Part 34	0.009464	0.02439
Part 35	0.018927	0.02439
Part 36	0.009464	0.02439
Part 37	0.031546	0.02439
Part 38	0.042587	0.02439
Part 39	0.018927	0.02439
Part 40	0.009464	0.02439
Part 41	0.003155	0.02439

And below table 3.4 shows the computed entropy at each station by the cases. In some stations, the entropy of case 2 is larger but subjects may feel easier than case 1. The reason is that the error proofing system supports decisions made by the subject through a guide monitor. The effect of the system is therefore considered by perceptual difficulty parameter of the fatigue effect index. The fatigue effect index is handled in the next step.

Table 3. 5 Informative entropy of each station

	Case 1	Case 2
S1	3.720926	2.352096
S2	4.815823	3.136128
S3	3.657638	2.744112
S4	4.436622	3.2668
S5	0.632726	0.522688
S6	3.359017	2.352096
S7	1.169177	1.045376
S8	2.025154	1.176048
S9	2.789154	2.221424
S10	3.948722	3.005456
S11	3.039743	2.090752
S12	0.982305	1.045376
S13	4.313585	3.92016
S14	3.648297	3.789488

Table 3. 6 Result of Regression

Source	DF	SS	MS	F	P
Regression	1	91225	91225	246.51	0.00
Residual Error	166	61431	370		
Total	167	152656			
S = 19.2371	R-Sq = 59.8%	R-Sq(adj) = 59.5%			

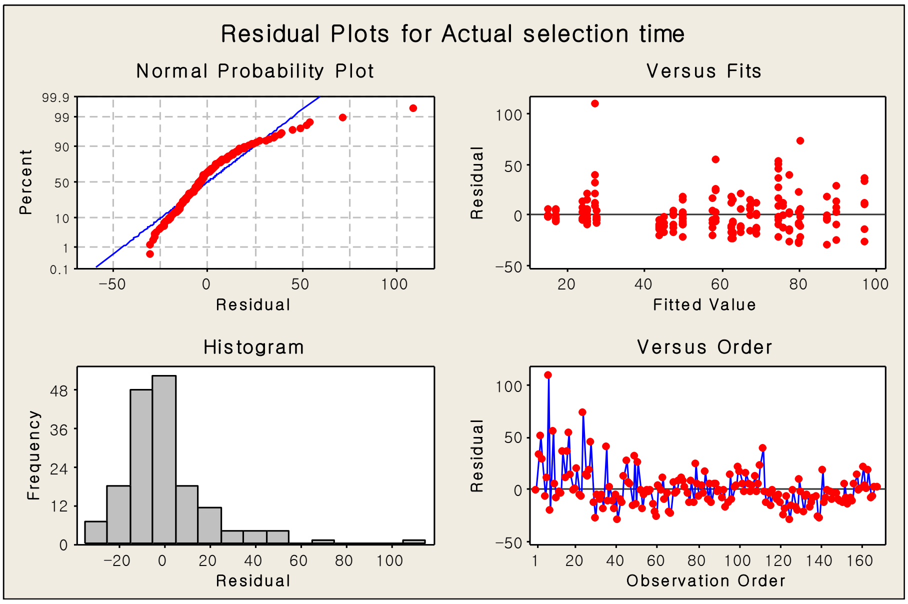


Figure 3. 7 Residual plots for actual selection time

After the entropy computation, the reliability of each case can be calculated by the entropies, cycle times, and assembly times, reaction times to select right part, and fatigue effect index. The entropies are computed and cycle times are set as 1.2 times the average processing times of each station. Reaction time is computed by the entropy and ergonomic parameters as $T_s^i = a + bH^i$. The ergonomic parameters are defined by regression of processing times and entropies and the ergonomic factors are defined as $a = 5.24, b = 19.1$. Next, to define the fatigue effect, difficulty parameters are needed. Physical difficulty is ignored because the part selection processes are concentrated and the parts are small enough to ignore physical issue. To find the perceptual parameters, various methods are applied and the parameter is set as $d = \frac{Standard\ deviation\ of\ part\ selection\ time}{100}$. The reliabilities and performances of each station are shown in table 3.5. The performance means that the rate of completed processes within a given cycle time. As shown in table 3.5, the reliability have a similar pattern with performance and the Pearson correlation coefficient is 0.626. Though the number of experiments is insufficient, the result shows meaningful consequences to validate the proposed model.

Table 3. 7 The reliabilities and performances of each station

	Case 1		Case 2	
	Reliability	Performance	Reliability	Performance
S1	0.4544	0.3333	0.8166	1.0000
S2	0.3780	0.3333	0.7692	1.0000
S3	0.5244	0.3333	0.7947	1.0000
S4	0.4303	0.3333	0.7494	1.0000
S5	0.8791	0.5000	0.9439	0.8333
S6	0.4760	0.5000	0.7928	0.8333
S7	0.8845	0.5000	0.9399	1.0000
S8	0.5725	0.3333	0.8814	0.8333
S9	0.6144	0.5000	0.8226	1.0000
S10	0.4690	0.5000	0.7583	0.8333
S11	0.4672	0.5000	0.7939	1.0000
S12	0.8506	0.6667	0.8943	0.5000
S13	0.4321	0.6667	0.6499	0.8333
S14	0.5634	0.5000	0.6828	0.8333

In this thesis, the proposed complexity model is designed considering informative entropy, the reliability of the operator's decision making process, and difficulty issues in manual assembly. But, in real manufacturing fields, production plan and ratio can change on a very short term basis. Consequently, the number of assembly parts can also change, although operators do not mind. So, computing the probability function and the entropy model can be simplified as follows:

$$H = \sum_{i} H(X^i) = -\sum_{i}\sum_{j}\sum_{k} P(x_{j,k}^i)\log_2 P(x_{j,k}^i)$$

$$P(x_{j,k}^i) = M_j^i \cdot O_k^i \quad where:$$

$\mathrm{H}(X^i)$: Informative entropy at station *i*.

$p(x_{j,k}^i)$: Probability for option *k* of model *j* at station *i*.

X^i : A set of variables inducing the uncertainty at station *i*.

$x_{j,k}^i$: A set of variables inducing the uncertainty for option *k* of model *j* at station *i*.

$x_{j,k}^i \in X^i$, $x_{j,k}^i = \{M_j^i, O_k^i\}$

M_j^i: Model ratio for model *j* at station *i*.

O_k^i: Option ratio for option *k* at station *i*.

4. Exploratory case study: Automobile body assembly processes.

4.1 Process setting

In the main body assembly line of automotive manufacturing industry, there are lots of cases in which operators encounter manufacturing complexity. Because of customer needs, environmental problems, government regulations, and different policies by countries, the products have different logos, colors, shapes of side mirrors, position of driver’s seat, functional devices, and so on. In addition, there are numerous causes which make operators feel complexity such as the variety of products, limited time, and ergonomic issues in the assembly process. For this reason, this section handles process configuration of the main body assembly line. All data sets used in this section are realistic data gotten from engineers in an automobile manufacturing company. In this case study, the data considered to compute the complexity are the tasks of each station, a model production ratio, an option production ratio, cycle time, and actual assembly processing time. And the other parameters are assumed as uniform for every station, because the production plan is changed at very short notice in real manufacturing fields and operators do not consider that to be very important. Detailed explanations of each parameter are treated in the computation process.

In this study, the target system consists of sixteen stations which are serially connected. And there are two types of model and sixteen types of option in the assembly line. The number and types of models/options are applied for each station. Table 4.1 shows the applied options and the cycle time of each station, and table 4.2 describes the probabilities depending on model, option, and station. As basic assumption in this study, all operators are identical and they make standard performances in every station. In this target system, the tact time is fifty five seconds and operators do not exceed the time limitation. If an operator exceeds the tact time in any station, then all the other stations are also delayed which leads to an unexpected cost as a downtime.

Table 4. 1 Cycle time of each option, model, and station

Station	S1		S2		S3		S4		S5		S6		S7		S8		S9		S10		S11		S12		S13		S14		S15		S16	
Model	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Opt1	47.10	45.84	54.48	12.88	30.42	7.38	37.02	30.18	37.42	17.04	27.30	11.10	18.68			17.34	49.34	48.68	48.68	48.32	42.14	42.14	42.14	42.14	0.84	36.72	0.84	36.72	0.84	1.04	37.62	0.84
Opt2				9.35		4.62		6.75		6.73		8.96				7.90																
Opt3				25.50		10.62		5.21		11.75		7.59				10.56																
Opt4						0.38																										
Opt5							4.57				3.73		7.37																			
Opt6																																
Opt7											5.25	8.96				7.90																
Opt8											4.94		4.89																			
Opt9											0.90																					
Opt10												8.28					3.52	1.71														
Opt11													2.38			7.36			0.86	2.67												
Opt12																									34.18		34.18		29.91			
Opt13																													14.62			
Opt14																														7.42		
Opt15																														6.11		
Opt16																																

Table 4. 2 Probability of each option, model, and station

Station	S1		S2		S3		S4		S5		S6		S7		S8		S9		S10		S11		S12		S13		S14		S15		S16	
Model	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Opt1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00			1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Opt2					0.43	0.43		0.43		0.43		0.43				0.43																0.43
Opt3					0.57	0.57		0.57		0.57		0.57				0.57																0.57
Opt4						0.10																										
Opt5							0.41				0.41		0.41																		0.41	
Opt6																																
Opt7											0.35	0.43				0.43																0.43
Opt8											0.81		0.81																			
Opt9											0.05																					
Opt10												0.39					0.80	0.39														
Opt11													0.20			0.61			0.20	0.61												
Opt12																									0.94		0.94		0.94			
Opt13																													0.97			
Opt14																														0.32		0.57
Opt15																														0.25		0.43
Opt16																															0.34	

4.2 Entropy computation

As already mentioned, the target system is a mixed-model assembly line designed in serial. So, the informative entropy of the system is computed by summation of the individual entropy of each station. In this case study, variants of parts, bolts, nuts, and tools are not considered because, in real manufacturing fields, production plan and ratio are changed within a very short term. And, depending on that, the number of assembly parts can be also changed, though operators don't consider that to be very significant. Furthermore, most of the variants are dependent on model and options of the product. So, in this section, the probability function is composed of a model ratio and option ratio of each station.

The entropy computation process follows these steps and table 4.3 shows the computation result of this system.

$$H = \sum_i H(X^i) = -\sum_i \sum_j \sum_k P(x^i_{j,k}) \log_2 P(x^i_{j,k})$$

where $x^i_{j,k} \in \{M^i_j, O^i_k\}$ and $/(x^i_{j,k}) = M^i_j \cdot O^i_k$. Once all required data of the process information are gathered, the procedure taken in this calculation are as follows:

STEP 1. Calculation of the probability mass function of outcome $x^i_{j,k}$ by the demand of model and option at each station.

STEP 2.Calculation of the sum of entropy at station i.

STEP 3. Calculation of the sum of the entropy gained by STEP 2 through all stations and options.

Since a close study of the similarity and proximity of the hardware resources lies outside the scope of this study, basically the weight of all random variables are set at one. Furthermore, the engine outfit process is too small a fraction of the whole manufacturing process to impose the weight of random variables.

Table 4. 3 Entropy of each station and model

Station	M1	M2
S1	0.114024	0.297041
S2	0.114024	0.675545
S3	0.114024	0.730938
S4	0.644561	0.675545
S5	0.114024	0.675545
S6	1.685698	0.835057
S7	1.404741	0
S8	0	0.892698
S9	0.439207	0.456553
S10	0.560531	0.514193
S11	0.114024	0.297041
S12	0.114024	0.297041
S13	0.298184	0.297041
S14	0.298184	0.297041
S15	0.442526	0.551315
S16	1.167874	0.675545

4.3 Reliability computation

As a basic concept of the model, the reliability of the system represents how well an operator complete right processes within a given cycle time in the assembly line. When an operator causes an error that the operator don't the complete processes within own cycle time, the effects of the error influence the other stations such as delay of overall production flow. This bottleneck problem is more critical in serial assembly line. For example, if the error occurs frequently at certain stations, then the impact of the problem also becomes greater. In this case, certain stations may have low reliability and can be defined as bottleneck in complexity measures. In the example, if a manufacturing engineer can estimate the complexity and reliability of the system, then the engineer might be able to prevent the error beforehand.

After the entropy computation, the reliability can be computed by proposed model in Chapter 3. As a basic concept of the model, the reliability of the system represents how well an operator completes the right processes within a given cycle time in the assembly line. To compute the reliability, the entropy of the system, time variants including cycle time, ergonomic parameters and difficulty parameters are needed. But, to define the ergonomic and difficulty parameters, extra surveys are necessary and it is a sensitive issue between labor and management in the real manufacturing industry. So, in this case study, physical difficulty is ignored and all the operators make a homogeneous performance to the same task. Additionally, ergonomic parameters are set as identical constants and all of the computations are arranged under the assumption that every station does not have any extra framework to support operators' decision making processes.

Results of the computation are shown at table 4.4. The reliabilities of each station and overall stations represent statuses of the stations whether performance of the system is reliable. As shown in table 4.4, processes of station 6, 7, 8, and 16 may have some problems to trigger the manufacturing complexity and additional solutions are needed to mitigate the complexity. And, in real manufacturing system, the solutions might be already applied by a trial and error approach. However, if manufacturing engineers could estimate the complexity before applying a design of the system, then the complexity can be mitigated without unnecessary cost.

Table 4. 4 Reliabilities of each station and overall stations

Station	M1	M2	Total
S1	0.99925	0.94337	0.99105
S2	0.99935	0.74856	0.99884
S3	0.99884	0.49482	0.94188
S4	0.97315	0.72035	0.90066
S5	0.99905	0.67762	0.95904
S6	0.83208	0.55551	0.68265
S7	0.85097	0.00000	0.85097
S8	0.00000	0.57160	0.57160
S9	0.99010	0.88224	0.96262
S10	0.98287	0.85467	0.94352
S11	0.99916	0.93855	0.99003
S12	0.99916	0.93855	0.99003
S13	0.99311	0.92981	0.97512
S14	0.99311	0.92981	0.97512
S15	0.98831	0.53173	0.94397
S16	0.90593	0.25712	0.78220

4.4 Additional application case study

The reliability based complexity model can have a roll of decision support tools as shown in the previous section. If this model can be successfully applied in the automotive manufacturing industry, then it can contribute to a growth of the industry. In this section, another expected application of the model is presented.

The reliability can anticipate the system's performance, which means the rate of completed processes within a given cycle time. In other words, the reliability can anticipate the error rate of the system and then it can approximately forecast wastes of the manufacturing system such as downtime in a mixed-model assembly line. In the assembly line, when an operator makes an error during the assembly process, the operator repeats the processes to fix the error. In such a situation, if the operator cannot complete the processes within a tact time of the station, the assembly line is stopped and delayed as much as the exceeded time, which is called downtime.

Table 4. 5 Expected downtime of each station

Station	Downtime(sec)
S1	0
S2	0
S3	0
S4	0
S5	0
S6	443.3151
S7	0
S8	178.418
S9	0
S10	0
S11	0
S12	0
S13	0
S14	0
S15	0
S16	0

In the data set handled in this chapter, there are tact time and cycle times of each station. And the proposed model can compute a reliability of the system. Then, the downtime might be able to estimated and the result of this application case study is shown at table 4.5.The table indicates an expected downtime per one hour at each station. And station 6, 8 are looked as bottleneck and have risks which delay an assembly processes. So, additional supporting systems are needed to prevent downtime at the stations.

5. Conclusion and future research

5.1 Conclusions and contributions

This study proposes a reliability based complexity model to estimate the manufacturing complexity of mixed-model production systems in the manufacturing industry. There is a lot of research estimating manufacturing complexity, with various approaches, and some of them contribute to the proposed model of this thesis. But, most of the research that concentrates on scholarly approaches and efforts for application are relatively insufficient in the real manufacturing industry. So, as one of the efforts, this thesis proposes the reliability based complexity model and shows a case study of the model with real manufacturing information data.

To design the model, the informative entropy (Shannon 1948, Zhu 2008) and reliability models (Wang 2010) were used as the theoretical basis, and manufacturing difficulty was considered as a key factor of the fatigue effect. By the model, the reliability of assembly processes can be computed from the process information of the system. Based on the results, manufacturing engineers can get feedback on such things as the current status of an assembly line or on the efficiency of a redesigned system. Furthermore, with accurate and specific process information, the model can forecast unintended costs or errors in the system. For example, as shown at chapter 4, the model can anticipate downtime caused by mistake operator error in the mixed-model assembly line.

The automotive industry is one of the representative industries which have complicated processes in the engineering field. For this reason, estimation of the manufacturing complexity is more significant and it can contribute to the growth of the automotive industry. The proposed model can provide an opportunity to optimize manufacturing systems as a decision support tool.

5.2 Future research

The result of this case study shows that our new reliability model presents reasonable calculations of the process’s complexity level. However, there are several parameters which need additional research, such as difficulty parameters. And the informative entropy can be developed with considering similarity. In addition, there are still lots of factors that affect the complexity such as working space, product design etc. and there are various manufacturing industries in addition to the automobile manufacturing industry. So, future research needs a multifaceted viewpoint, such as a detailed study to define manufacturing difficulty, and a macroscopic study to apply the model to other manufacturing industries.

Therefore, as a future study, there are two primary approaches that first one is study of the manufacturing difficulty to fine-tune the reliability based complexity model. The manufacturing difficulty could affect the reliability and performance of the system, and this paper suggests an approaches to model the relationship between them. But, it is still insufficient to define the model and more research is required to modify that. And the other one is an application study. As mentioned previous chapter, the proposed model can be a competitive tool in the manufacturing industry. But, the model cannot be applied to actual work-sites yet as it is needed to be fine-tuned by various application studies.

Reference

1. ElMaraghy, W., H. ElMaraghy, T. Tomiyama, and L. Monostory. 2012.“Complexity in Engineering Design and Manufacturing.” CIRP Annals–Manufacturing Technology61 (2): 793–814.
2. Suh, N. P. 2005a.“Complexity in Engineering.”CIRP Annals–Manufacturing Technology54 (2): 46–63.
3. Suh, N. P. 2005b.Complexity: Theory and Applications. Oxford University Press.
4. Frizelle, G., and E. Woodcock. 1995.“Measuring Complexity as an Aid to Developing Operational Strategy.”International Journal of Operations & Production Management15 (5): 26–39.
5. Deshmukh, A., J. Talavage, and M. Barash. 1998.“Complexity in Manufacturing Systems–Part 1: Analysis of Static Complexity.” IIE Transactions 30: 645–655.
6. Efthymiou, K., A. Pagoropoulos, N. Papakostas, D. Mourtzis, and G. Chryssolouris. 2011.“Manufacturing Systems Complexity an Assessment of Manufacturing Performance Indicators Unpredictability, (DET 2011).”In: 7th International Conference on Digital Enterprise Technology, Athens, Greece, 383–391, ISBN 978-960-88104-2-6.
7. Efthymiou, K., A. Pagoropoulos, N. Papakostas, D. Mourtzis, and G. Chryssolouris. 2012.“Manufacturing Systems Complexity Review: Challenges and Outlook.”(CIRP-CMS2012) 45th CIRP Conference on Manufacturing Systems, Athens, Greece, Procedia CIRP, vol. 3, 644–649.
8. Zhu, X., S. J. Hu, Y. Koren, S. P. Marin. 2008. Modeling of manufacturing complexity in mixed-model assembly lines. Journal of Manufacturing Science and Engineering 130(5).
9. Wang, H. 2010. “Product variety induced complexity for mixed-model assembly systems and supply chains.” Mechanical Engineering and Industrial and Operations Engineering in The University of Michigan
10. Lee, W. (2015). Analysis of Manufacturing Complexity for Optimal Resource Allocation in Mixed Model Production of the Automotive Industry.
11. Fujimoto, H., Ahmed, A., Iida, Y., and Hanai, M., 2003, “Assembly Process Design for Managing Manufacturing Complexities Because of Product Varieties,” International Journal of Flexible Manufacturing Systems, 15(4), pp. 283–307
12. Kahn, B. (1998), “Dynamic relationship with customers: High-variety strategies”, Journal of the Academy of Marketing Science, Vol. 26, No. 1, pp. 45-53.

13. F Midler, C. (2005), “Innovation Based Competition in Auto Industry: New Challenges for Design Organization and Co-Innovation Processes”, IMVP-MMRC Conference, Hosei University, Tokyo, October 13 2005.
14. Urbanic, R Jill, & ElMaraghy, Waguih H. (2006). Modeling of Manufacturing Process Complexity Advances in Design (pp. 425-436): Springer.
15. Cooper, W.W., Sinha, K.K., Sullivan, R.S., 1992, “Measuring Complexity in High Technology Manufacturing: Indexes for Evaluation,” Interfaces, pp. 38-48.
16. Koren, Y. 2010. The Global Manufacturing Revolution: Product-Process-Business Integration and Recongurable Systems . John Wiley & Sons.
17. Shannon, C. E., “A Mathematical Theory of Communication,”The Bell System Technical Journal,Vol. 27, pp. 379–423 (July 1948).
18. Kuhn, Thomas S. (1961). Sadi Carnot and the Cagnard engine. Isis, 567 -574.
19. Shannon, Claude Elwood, & Weaver, Warren. (1948). A mathematical theory of communication: American Telephone and Telegraph Company.
20. H. Wang, S.J. Hu, “Manufacturing Complexity in Assembly Systems with Hybrid Configurations and Its Impact on Throughput", CIRP Annals-Manufacturing Technology 2011. Volume 59, Issue 1, 2010, Pages 53–56
21. Papakostasa N., Efthymioua K., Mourtzis D. (2009) Modelling the Complexity Of Manufacturing Systems Using Nonlinear Dynamics Approaches,Annals of the CIRP58(1): 437–440.
22. Webbink RF, Hu SJ (2005) Automated Generation of Assembly System Design Solutions.IEEE Trans on Automation Science and Engineering 2(1):32–39.
23. Yang, M., J. Gao, B. Zhao, X. Huang, Z. Shen. 1997. Study of operator reliability in nuclear power plants. Chinese Science Bulletin 42(19) 1585-1590.
24. Hyman R (1953) Stimulus Information as a Determinant of Reaction Time. Journal of Experimental Psychology 45:188–196.
25. Bystrom S, Fransson-Hall C (1994) Acceptability of Intermittent Handgrip Contractions Based on Physiological Response.Human Factors36(1):158–171.
26. Marcora SM, Staiano W, Manning V (2009) Mental Fatigue Impairs Physical Performance in Humans.Journal of Applied Physiology 106:857–864.
27. Cover, T. M., J. A. Thomas. 1991. Elements of Information Theory . 2nd ed. John Wiley & Sons
28. Deshmukh, A. V., J. J. Talavage, M. M. Barash. 1998. Complexity in manufacturing systems, part 1: Analysis of static complexity. IIE Transactions 30(7) 645-655.
29. ElMaraghy, H. A., O. Kuzgunkayaa, R. J. Urbanic. 2005. Manufacturing systems conguration complexity. Annals of the CIRP 54(1) 445-450.

30. Fisher, M. L., C. D. Ittner. 1999. The impact of product variety on automobile assembly operations: Empirical evidence and simulation. Management Science 45(6) 771-786.
31. Karl Pearson. 1895, Notes on regression and inheritance in the case of two parents," Proceedings of the Royal Society of London, 58 : 240–242.
32. Koren, Y., S. J. Hu, T. W. Weber. 1998. Impact of manufacturing system congurations on performance. Annals of the CIRP 47(1) 369-372.
33. Zhu, X. (2009). Modeling product variety induced manufacturing complexity for assembly system design (Doctoral dissertation, General Motors).
34. Boysen, N., Fliedner, M., & Scholl, A. (2007). A classification of assembly line balancing problems. European journal of operational research, 183(2), 674-693.

Acknowledgement

Above all, I really appreciate my advisor, professor Nam-hun Kim, for his support and guidance. I may be not able to complete the master course and finish this dissertation without his help. Thanks to the help, my capability can be developed and I can also learn many knowledge, scientific approaches and researcher's attitudes in the master course. Most of all, he always encouraged my study and guided me to right ways even if I committed a critical mistake. And I also want to say "thank you" to my other committee members, professor Seung-Chul Lee and Sung-Youb Kim, who gave me boundless encouragement and support. Without their help, I would have a lot of troubles in my scholarship.

Additionally, I would like to thank all members of U-CIM lab and 3DAM, Woo-Yeol Lee, Woon-Song Yeo, Eun-Ju Park, Kasin ransikarbum, Ju-Yeon Kwon, Yeong-Gwang Oh, Moise Busogi, Sang-Ho Ha, Jeong-Sik Kim, Hwee-Young Han, Dong-Hwan Song and all the other members. "Thank you all. I can enjoy a life in laboratory and I was happy because of you." They are my vitamin for researching routine and they always cheered me up when I exhausted or frustrated.

Finally, I want to give my greatest thanks to my family. They absolutely respect and believe my decision in my life. Furthermore, they have supported me with all their way. So, I want to give my all gratitude to my family. "Thank you and I love you. I could not complete anything and cannot do anymore without your love".